Mesoscale Predictability and Improving the Utility of Ensemble Forecasts

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PROJECT GOALS AND OBJECTIVES

The PI and Co-I are examining mesoscale predictability with the goal of improving the utility of ensemble forecasts (EFs) at ranges of 12 hours to 2 days. Our research addresses the issues of initial condition uncertainty (ICU) for mesoscale analyses and the merit of calibration of output from ensemble prediction systems (EPSs) by artificial neural networks. The PI also serves as Chief Scientist to Dr. Scott Sandgathe for ONR initiative on Predictability in the Atmosphere and Ocean.

DOCUMENTATION OF ANALYSIS UNCERTAINTY

Despite years of ongoing research, there is still spirited debate on how to generate initial perturbations for medium-range EPS's with global models. Research on perturbation design for mesoscale limited-area models is, at best, in its infancy. It is clear however, that whatever strategy is employed (dynamic or statistical), initial perturbations must be properly constrained by our best estimate of analysis uncertainty.

Several approaches come readily to mind. The ideal approach would be the successful integration of the data assimilation system (DAS) and the EPS, a so-called extended Kalman filter (Houtekamer and Mitchell 1998). Another approach would be Observing System Simulation Experiments (OSSEs) with a four-dimensional operational DAS, which is perhaps the best, *proven* way to address the problem. A third method would be a thorough documentation of analysis-analysis differences from different

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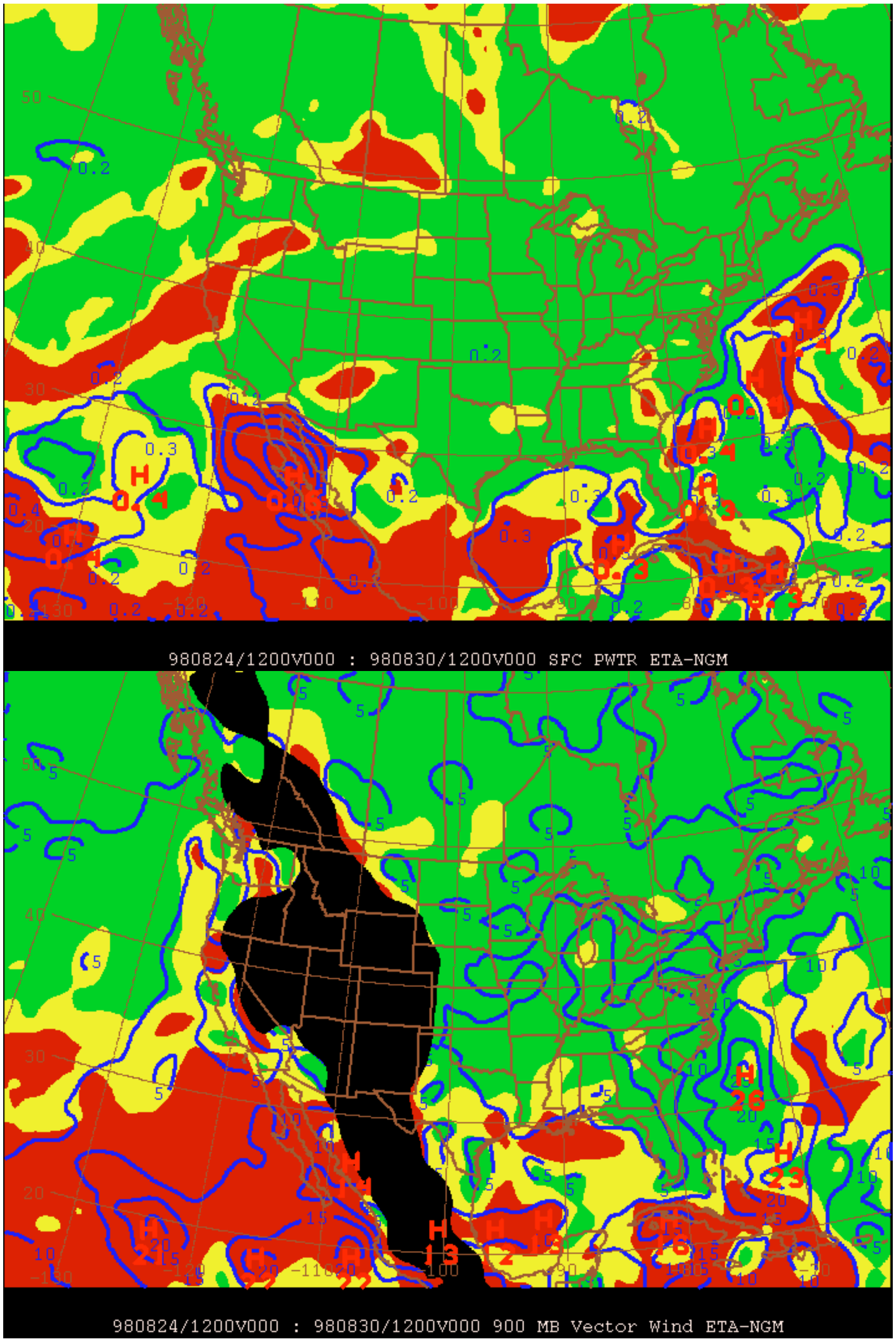

Figure 1: Standard deviation of differences between the ETA and NGM initial analyses during the period 1200 UTC 24 August 1998 to 1200 UTC 30 August 1998. Precipitable water (top, CI: 0.1"); 900 mb vector wind (bottom, CI: 5 knots). Color fill denotes the ratio of variance of analysis differences to the variance of the ETA analysis: values < 0.5 (green), values between 0.5 and 1.0 (yellow), values > 1.0 (red). Black shading masks areas where model fields are below the ground.

analysis-forecast systems. This approach defines a “component" of the analysis uncertainty. Although this methodology is not as insightful as an integration of the DAS and EPS or a comprehensive OSSE, it is currently tractable, very economical, and useful guidance can be quickly obtained.

The PI is comparing differences between NCEP LAM analyses from the NGM (Hoke et al. 1989) and ETA (Rodgers et al. 1995) model. It is important to consider LAM fields since scales not resolved by global analyses are presumably analyzed with greater certainty over the data rich, North American continent. Figure 1 shows the standard deviation of differences between the ETA and NGM analyses for the period 24-30 August 1998. Plots are shown for the precipitable water, 900 mb temperature, and 900 mb vector wind. The dominant synoptic features during the period were hurricanes Bonnie along the East Coast, Danielle over the Bahamas, and Howard in the eastern Pacific. Note that these regions are characterized by large absolute uncertainty, consistent with the conventional notion that analyses are more uncertain near regions with growing disturbances. In fact, the normalized variances exceed unity over the tropical oceans, which indicates the information content of tropical analyses for the period is questionable at best.

NEURAL NETWORK POST-PROCESSING OF ENSEMBLE FORECAST PRODUCTS

Because forecast fields produced by any NWP model always contain errors due to model deficiencies (e.g. lack of resolution, inadequate parameterizations, truncation error, etc), raw model output is often statistically post-processed to mitigate their impact. Post-processing also provides a way to relate model output fields to weather elements not explicitly forecast by the NWP model (e.g. visibility, probability of thunder).

There are many viable ways to generate statistical forecasts and calibrate NWP model (e.g. Marzban and Stumpf 1998). The technique currently in use at NCEP (e.g. Carter et al. 1989) is Model Output Statistics (MOS). MOS is based on multiple linear regression (MLR) and typically reduces the error variance by 20%. To yield stable statistics, MOS requires a data set of several seasons for training that is averaged over a broad geographic region, and it typically involves the screening of a couple hundred predictors. The need for such long training data sets is a major shortcoming MLR.

The calibration of EPS output presents even greater challenges than deterministic forecasts because of increased dimensionality of the output. Recent results indicate that strategies besides MLR can be employed for EPS output with equal success (e.g. Hamill and Colucci 1998), methods that correct for biases and under or over dispersion of ensemble spread and require much shorter training periods than MOS.

The mature fields of digit signal processing and artificial intelligence offer other possible paradigms to explore. Consider artificial neural networks (ANNs), computer algorithms designed for nonlinear optimization. Impressive applications of ANNs to remote sensing, atmospheric diagnosis and weather prediction are beginning to appear. A plethora of applications, mostly diagnostic or prognostic based on extrapolation from observations and analyses, recently appeared in the preprint volume of AMS First Conference on Artificial Intelligence (1998); an excellent overview of NN applications to operational forecasting is given by Christopherson (1998) in the said volume.

The calibration NWP output by NNs, though limited, are just as impressive (Eckert et al 1996, Hall et al. 1999). The PI’s (Mullen et al. 1999) extended ANN processing to QPF output from the pilot ETA/RSM ensemble data set that was also used by Hamill and Colucci (1998). We found that

calibration of 12-24 h rainfall totals at stations with a back propagating ANN, trained with just 12 independent case days, was competitive with MOS. Results (Mullen et al. 1999, in preparation) obtained during this summer under ONR support are shown in Fig. 2. Note that the 0.10” threshold exhibits close to perfect reliability. Even the 0.25” threshold (not shown), trained by a sample with only 240 episodes of 0.25” or greater out of 3900 total reports, shows improvement over MOS, with nearly perfect reliability for probabilities of 70% or lower. The refinement portion of the diagram (not shown) shows that the 0.01” and 0.10” thresholds are sharp, but the 0.25” threshold with no 100% forecasts is not as sharp.

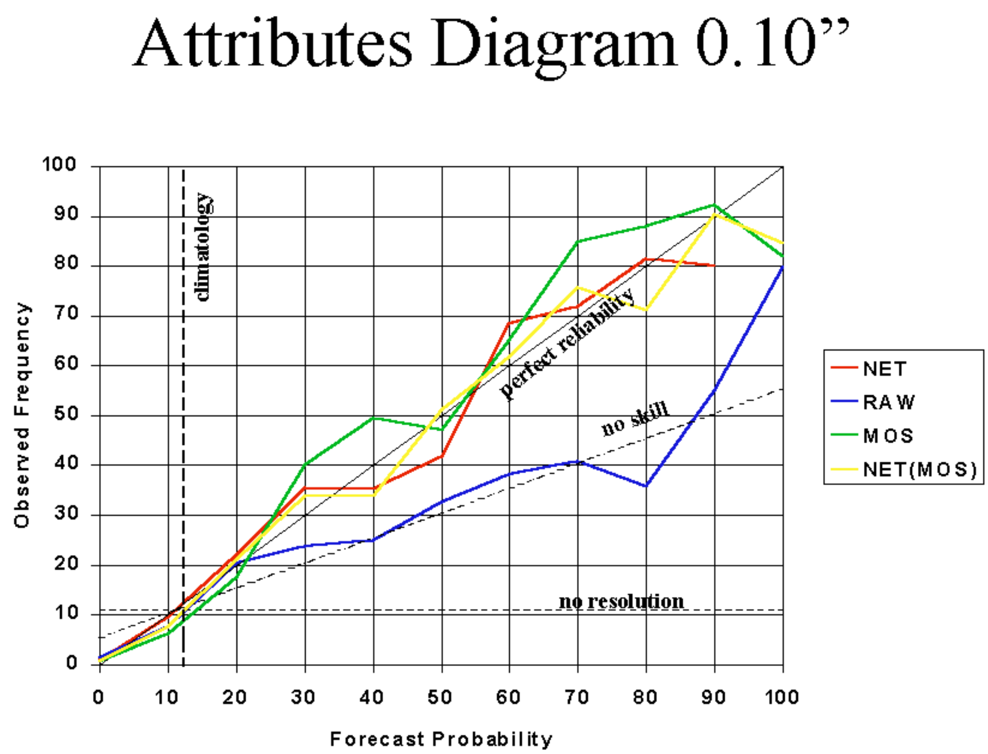

Figure 2. Reliability diagrams for the 0.10” threshold. Shown are results for the RAW ensemble (blue), NET processing of the ensemble (red), MOS (green), and NET processing of MOS (yellow).

Under ONR support in FY99, the PI and Co-I will further examine the robustness of ANN processing of EPS output. We will 1) screen predictors and predictands other than precipitation, 2) train in one geographic region and test in another and 3) processing two modeling systems, a global model and a mesoscale LAM. We anticipate that NN processing of the global and mesoscale LAM EPS output will yield improvements in accuracy comparable to those reported by Hall et al. (1999).

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